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# A holistic approach to PLI in Smart Maintenance towards sustainable Manufacturing

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**Abstract.** With the digital transformation of the maintenance function with emerging technology such as machine learning, Smart Maintenance will contribute to increased plant capacity as well as reduced maintenance costs. Profit Loss Indicator (PLI) has been tested for preventive maintenance combined with anomaly detection. Yet, it remains to include PLI into Smart Maintenance processes to ensure standardized application. PLI will also contribute towards sustainability in terms of improved production performance through reduced waste and time losses. This will also contribute to an improved working environment. The aim of this article is therefore to develop a smart maintenance process for PLI. This article demonstrates the main processes of smart maintenance that are harmonized with EN 17007 and sustainability. In addition to PLI, a hybrid approach for anomaly deployment as well as a dynamic FMECA (failure mode, effect and criticality analysis) are included in Smart Maintenance. Also, the result is partly tested where PLI is calculated for a Norwegian use-case. It is concluded that more elements for the smart maintenance processes must be further modelled and tested with industrial use-cases.

**Keywords:** Smart Maintenance, Profit Loss Indicator, sustainability.

## 1 Introduction

With more commercial sensor technologies available on the market such as wireless sensors, predictive maintenance (PdM) is considered to contribute to reducing downtime and saving operational costs [1]. It is expected that PdM will digitally reshape several industry branches in terms of deployment of a predictive maintenance strategy [2]. In particular, the indicator profit loss indicator (PLI) has been applied and tested for PdM based on machine learning (ML) application in maintenance planning [3]. The sustainable digitalisation in PdM will require a change in the maintenance function towards Smart Maintenance that includes data-driven decision making with both human and capital resources [4], as well as dynamic failure mode, effect and criticality analysis (FMECA) [5].

In addition to the technology development outlined in the mission statement for digitalization, the sustainability is also clearly elaborated in terms of e.g. better work life as well as climate protection [2]. In fact, Smart Maintenance contributes towards sustainability in e.g. human-machine training [6].

In order to allow for PdM, machines and equipment are monitored for condition and faults [7]. Using sensor data, pattern recognition, failures and events, anomalies are detected using methods such as equipment-specific algorithms (1), ML techniques (2) and small-scale lab collected data (3). Implementing the PdM methodology in an I4.0 environment will require considerable work developing data structure and architecture to allow for near real-time analytics, Big Data methods, data quality, data security and data integration [7] [8]. ML methods are dominant in terms of published papers, but there are some more critical towards ML methods, highlighting areas like “black-boxing”, trust issues, data availability and scaling issues [8] [9]. Proposed solutions to AI-method challenges include “Explainable AI” and hybrid methods, using both ML and classical statistical methods [10] [11]. A “toolbox” of classical methods that can be employed in complex, multivariate environments includes Principal Component Analysis (PCA), that can be used to detect anomalies in large, multivariate datasets and as a data reduction strategy [11]. Thus, Smart Maintenance and PdM should also include a toolbox of classical methods in data-driven decision making.

To succeed with Smart Maintenance a “common language” is also required with particular contribution from the standard EN 17007 “Maintenance process and associated indicators” [12]. In PdM, a standardisation roadmap has also been developed and will contribute to standardisation [1]. It remains to investigate how EN 17007 will be aligned with PLI as a tool for Smart Maintenance. Although this standardisation work is expected to be rolled out in Europe, there are still several obstacles that must be evaluated in Norwegian Industry. One fundamental challenge is to have the correct competence, leadership and culture for measuring the losses in maintenance. Relevant challenges and existing initiatives towards Smart Maintenance in Norwegian industry is therefore of importance to address. Among others, the research project CM4Smart aims to develop Smart Maintenance for Norwegian industry.

The aim of this article is to develop Smart Maintenance process for PLI. The future structure in this article is as follows: Chapter 2 first presents the status of Smart Maintenance in Norwegian industry and then proposed smart maintenance process. Chapter 3 presents some results of Smart Maintenance processes based on an industrial use-case, whereas discussions and concluding remarks are made in Chapter 4.

## **2 Smart Maintenance**

### **2.1 The Maintenance Function in Norwegian Industry**

Despite that some companies in Norway represented by e.g. the smelting industry and manufacturing industry seem to be in front in developing Smart Maintenance, there is still a gap between ambitions and the reality. Traditionally, Norwegian industry has been focusing on corrective maintenance. A challenge may also be the accuracy of data that has been manually collected. Yet, today this industry is more focused on proactive

maintenance. Norwegian industry should learn even more from digitalization of maintenance from countries such as Germany [2] and Japan [6].

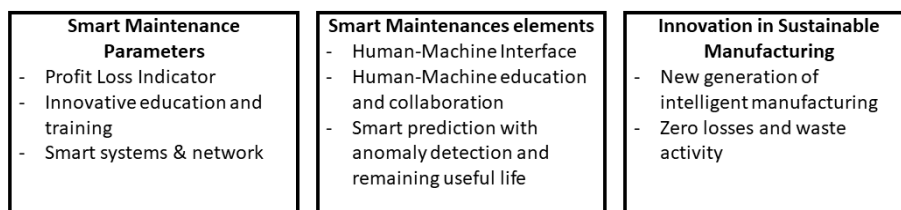
The Norwegian O&G industry has today implemented preventive maintenance programmes. For some new equipment types such as rotating equipment, a high degree of condition monitoring is applied and can be further used for predictive maintenance. A portion of equipment at ageing facilities have little or no sensors for condition monitoring. Yet, these facilities have long data history of condition parameters that have been manually collected. These condition parameters can support maintenance planning. An example can be inspection results used for prediction calculations for equipment and facilities with low degree of automatic condition monitoring methods. It remains to align this experience in Smart Maintenance processes.

The CM4Smart project aims to develop and implement a Smart Maintenance concept within HTS maskinteknikk. In addition to developing, integrating and testing IoT-technologies, an important part is to align new technologies with a new way of thinking about maintenance. In its essence Smart Maintenance forces and motivates a company like HTS maskinteknikk to become more proactive. This implies that all personnel, from the management to the production employees are faced with the task of thinking more about risks and optimizing specific costs. Having access to real time data and a trustworthy PLI indicator will change maintenance scheduling and hopefully lead to increased uptime and utilization as well as lower overall maintenance cost. An online and connected PLI will help HTS maskinteknikk make faster and better decisions.

## 2.2 PLI and Smart Maintenance processes

PLI has its offspring from the “hidden factory” and the need for measuring time losses and e.g. calculation of overall equipment effectiveness (OEE) [13]. Today, an appropriate industry standard for OEE calculations exists [14]. PLI expands this OEE calculation and measures the hidden factory as a monetary indicator and includes ML [3].

Since PLI is founded on measuring time losses and waste in production it has a clear contribution to sustainability. In fact, the production industry with a more efficient production process can significantly reduce pollution and waste and contribute to a better working environment [6]. Figure 1 presents central main elements for sustainability inspired from [15].



**Fig. 1.** Key elements for sustainability, inspired from [15]

In addition to PLI in Figure 1, key elements for sustainability will also include innovation in activities that contribute to e.g. near zero losses and improved human-machine interfaces.

The standard for maintenance processes EN 17007 will provide an aid for the maintenance managers to compare their organisation by a generic description and detect any significant deviation [12]. The Maintenance processes are categorised into the following main categories:

1. *Management process*: Activities for determining the objectives and the policy to be implemented in the organisation.
2. *Realization processes*: These processes contribute directly to achieving the expected result expressed in terms of satisfaction by the customer.
3. *Support processes*: Processes that are essential to the support of the other processes and includes human, financial and material resources.

In Smart Maintenance, all these main processes will be affected. For data-driven maintenance it is of interest to investigate the support process “manage data” (DTA).

Both ML and statistical methods rely on high quality raw data from sensors. Sensor accuracy and drift must be accounted for before data pre-processing. Addressing these inaccuracies might be difficult using either ML methods or mathematical correction [16]. Using classical statistical methods like PCA can be utilized as standalone classical methods, or as part of a hybrid method [16] [17].

A proposed framework for smart maintenance processes using both classical and ML methods is shown in Figure 2, inspired by [18]. In this framework, processes for deploying anomaly detection as well as activities for PLI are identified.

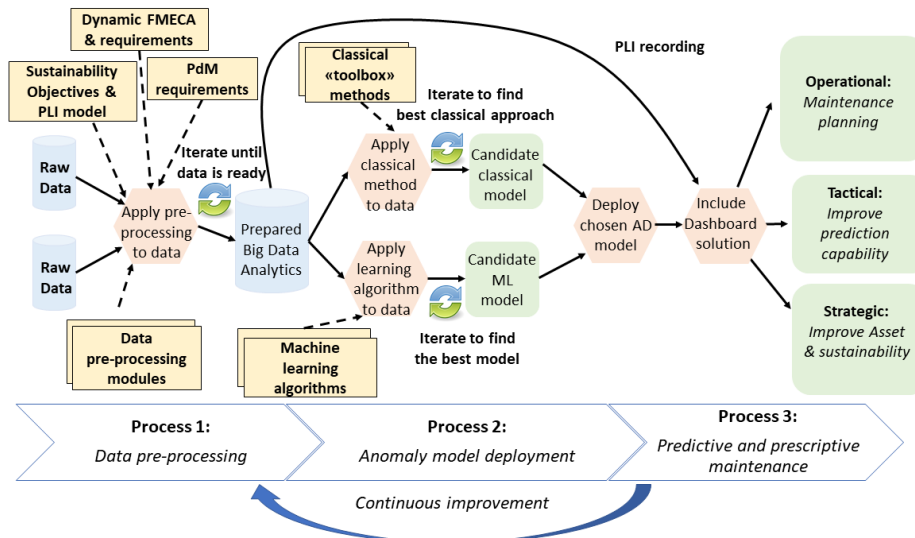


Fig. 2. Smart maintenance processes inspired by [18].

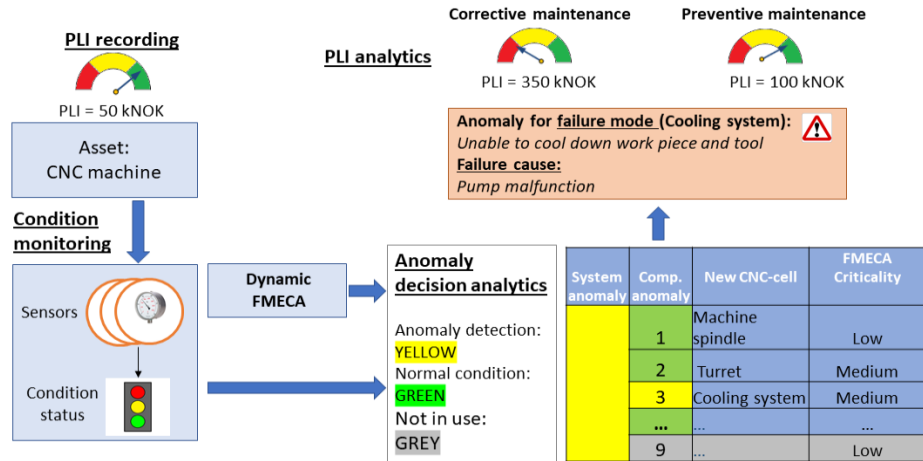
FMECA has a significant contribution in data-driven maintenance [5] and is therefore included in data pre-processing. The criticality can evolve over time due to e.g. usage conditions, the technological evolution or new skills acquired in the organisation [19]. With suitable digital platforms FMECA can support maintenance planning more in real-time instead of only during company-specific revisions. Table 1 further elaborates the Smart Maintenance processes. Predictive maintenance will include forecasts derived from analysis. Yet, Smart Maintenance incorporates several dimensions such as data-driven decision-making, human capital resource, internal integration as well as external integration [4].

**Table 1.** Description of Smart Maintenance processes.

Smart Maintenance process	Description of Smart Maintenance process	Elementary process in EN 17007
<b>Process 1:</b> Data pre-processing	<ul style="list-style-type: none"> <li>- Dynamic FMECA for data-driven maintenance</li> <li>- PdM requirements: required time horizon, accuracy</li> <li>- PLI Model and Sustainability objectives</li> </ul>	DTA.2: Evaluate the reliability and maintainability of the items by maintaining an actual state assessment of the items.
<b>Process 2:</b> Anomaly model deployment	<ul style="list-style-type: none"> <li>- Principal Component Analysis</li> <li>- Deep Learning</li> </ul>	
<b>Process 3:</b> Predictive and prescriptive maintenance	<ul style="list-style-type: none"> <li>- PLI recording</li> <li>- Remaining life evaluation</li> <li>- Operative, tactical &amp; strategic decisions</li> </ul>	DTA.11: Calculate, save and provide access to performance and monitoring indicators

### 3 Smart Maintenance process result

Figure 3 presents a storyboard for smart maintenance process 3 (predictive and prescriptive maintenance) for HTS maskinteknikk. Starting with PLI recording, it is possible to collect data for future maintenance decisions in terms of avoiding failures as well as improvement of the physical asset. By applying anomaly decision analytics combined with PLI and FMECA, it is possible to evaluate possible future maintenance actions in terms of preventive and corrective maintenance. The further use-case describes the PLI recording at the company.



**Fig. 3.** Storyboard for smart maintenance process

The use case is a state-of-the-art CNC cell with the following main functions: raw material handling and storage, material transport/movement, CNC-tending, machining/turning, cleaning, measurement and tool correction, monitoring and reporting.

This CNC cell in the use case is executing important work orders for the company and is a strategic implementation of state-of-the-art technologies available on the market. It is a “signal project” within the company, meaning that it represents what can be done today to increase productivity and efficiency. The CNC-cell is planned to be operated with few to no production technicians due to the level of automation and monitoring implemented. This means that the company must rely on the IoT monitoring systems to notify if something goes wrong or if anomalies are detected. All this to allow the company to act fast and to fix and ensure required output. The ROI demand for this cell is high due to the high acquisitions.

Table 2 summarizes the PLI elements included in the use-case and should illustrate PLI for one arbitrary week. The PLI categories are based on time loss categories from OEE calculations [13].

**Table 2.** PLI categories measured in use-case

Loss category	Turnover loss content	PLI value [NOK]
<b>Availability</b>	<i>Shutdown loss (1), Breakdown and failure loss (2), Setup- and adjustment loss (3), Tool replacement loss (4), Start-up loss (5) and other Downtime Losses such as waiting for materials (6)</i>	11.000
<b>Performance</b>	<i>Minor stoppages and idling (7) and Speed loss (8)</i>	4.000
<b>Quality</b>	<i>Quality defect and rework loss (9)</i>	3.500
<b>Utilization</b>	<i>Not scheduled (10) and Unscheduled (11) (Overcapacity)</i>	75.000
<b>TOTAL PLI</b>		<b>93.500</b>



## 4 Discussion and concluding remarks

This article has developed 3 main processes for Smart Maintenance and partly tested these in Norwegian Industry. To reshape a company towards Smart Maintenance the organisation must still conduct the fundamental maintenance functions where e.g. the time losses are measured before calculating PLI. This will require accurate time loss registration for computation and integration into the digitalized maintenance systems and the IoT system at HTS. The short-term aim for HTS maskinteknikk is to implement smart maintenance including a plant wide FMECA project. The plan long term is to further change the mindset from “have we done some service?” towards “what is the current OEE and PLI in plant? How can we improve it?”. Also, this change will shift the focus from measuring breakdowns towards measuring minor stoppages.

For process 1 and 2 different methods have been proposed. Adding a “toolbox” of classical methods that can handle multivariate analysis can be beneficial when utilizing ML methods. A PCA analysis can help reduce the dimensionality of large datasets and help determine critical variables as part of data pre-processing. PCA can also help with detecting anomalies in multivariate processes. Both methods have been applied in a pilot experiment in the QU4LITY EU project in conjunction with ML methods to automate anomaly detection, and the results are promising. Some of this is related to the ability to include expert domain knowledge from the analysed processes and the transparency of utilizing classical methods.

For process 3 PLI has been tested in a use-case. For operational application this PLI recording will be used to measure e.g. significant downtime due to failure and breakdown. This can then be used for future maintenance planning.

Sustainable maintenance should be a holistic perspective on Smart Maintenance, incorporating PLI and Industry 4.0, and ensuring a balanced approach to sustainability through e.g. reduced PLI (economic), reduced use of raw material (environmental) and application of “ethical” AI in anomaly detection (social).

Finally, the closed loop must ensure continuous improvement for the smart maintenance processes. For example, PLI recording can also be used for strategic decisions where the physical asset is improved and PLI reduced.

To conclude, Smart Maintenance must be a holistic approach, and should include PLI, dynamic FMECA, PdM requirements, continuous improvement, sustainability objectives, a dedicated data structure, and a transparent classical statistical approach to support ML activities to improve maintenance planning, prediction capability, sustainability and the asset itself.

Further, HTS maskinteknikk will develop this framework with application of a more generic and dynamic FMECA and PLI. Also, PLI should be included as an indicator for sustainable manufacturing.

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